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Classification Of Surface Roughness Of End Milled 6061 Aluminum Alloy Components: Data Mining Approach

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Abstract-*Automatic classification of surface roughness of machined surface finds its application in product quality. Machine vision is used in the automatic classification of surface roughness of the end milled components. Machine learning approach to machine vision system helps in classifying image features of machined surface. The steps involved in this approach are component machining, surface roughness measurement, Image acquisition, Image preprocessing, feature extraction and classification. There are various data classifier are available in the literature, however the selection of best classifier yield higher classification accuracy. In this article, images of various cutting conditions such as speed, feed and depth of cut were acquired, preprocessed and features are extracted. The features were classified using C4.5 algorithm and Naïve Bayes algorithm and compared. The study result shows that C4.5 algorithm performs better.*

Keywords: Machine Vision, Data Mining, Feature Extraction, Image processing, Classifier, Surface roughness

I INTRODUCTION

Automation becomes a vital role in the manufacturing environment to sustain in the competitive market. Automation can be employed at various levels right from selection of raw material to the packaging of final product. In the process of automation, machine learning approach helps in imparting human intelligence to machines. The machine vision system is one of the solutions for automation of inspection process. The Machine vision system employs one of the following approaches namely pixel –based approach and feature-based approach. The image characteristics are derived from pixel values directly. However it requires high tuning and effort in deriving the characteristics of the image. The feature-based approach utilizes features extracted from the images for training a classifier and thus designing visual classification of surface roughness system.

Literature addresses many industrial situations namely detecting defective products [1]. The pixel- based approach is used for machine vision application to detect multiple defects such as scratches, scraps and bubbles occurring in glass and plastic production process [2]. The Machine vision system is employed in tool condition monitoring [3-5]. The above listed articles are based on pixel- based approach developed automated visual inspection system which are time consuming and trial and error basis. These drawbacks were overcome by feature-based approach with machine learning algorithms.

Literature study shows, there are various image features could be extracted under statistics and spatial frequency domain. Histogram features are extracted from surface images are used to classify the defects like deep scratch and Minor scratch [6]. Tamura features such as coarseness, contrast, directionality, line likeliness, roughness and regularity are used to classify rock images by Probabilistic Latent semantic analysis and sum of square difference classifier [7]. The spectrum parameter major peak frequency, standard deviation of gray level and the arithmetic average of the gray level were used to correlate between vision roughness and stylus roughness [8]. Gray Level Co-occurrence Matrix (GLCM) texture features were used to determine the suitable features for surface roughness quantification [9]. RMS features of the Acoustic Emission Signals with wavelet transform were used in classifying the grinding wheel wear with help of

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data mining classification technique called C4.5 algorithm [10]. The performance analysis on the classification algorithms was done on the data set with known class labels [11-12]. Decision tree based classification was performed in the prediction of surface roughness of laser polished components [13].

In this study, an attempt is made to use C 4.5 algorithm and Naïve Bayes algorithm in combination with GLCM features of the machined surface images for classifying surface roughness values. A CCD camera captures the image of the 6061 Aluminum alloy surface after end milling operation. The images are then sent for image preprocessing in order to obtain useful image data without the influence of noise. The GLCM Texture features are then extracted for various machined surface images. Surface roughness measurement was carried out to label classes. From the literature, the major problem here is to select the right feature- classifier combination. The main contribution of this article is of two phases. First, GLCM features were used for feature selection and classification using Machine learning C 4.5 algorithm. Then, in the second phase, Classification was performed using Naïve Bayes algorithm. The performance analysis of both algorithms was studied and reported.

II THE EXPERIMENTAL SETUP

The Experimental setup is designed for capturing surface images of 6061 aluminum alloy component prepared by end milling operation. The experimental setup used for this study was as shown in the fig .1 The arrangement consists of a CCD camera with zoom lens, a CPU with suitable software to capture and store the image.

A. Component preparation

6061 Aluminum alloy part of dimensions of 50mm x 50mm x 25 mm is machined using conventional vertical milling machine. HSS ϕ12mm twist fluted end milling cutter is used as cutting tool. Machining the aluminum alloy part was carried out at various level of cutting conditions. The following cutting conditions are chosen for this study;
Speed, Feed and Depth of cut.Table 1. Show the level of various cutting conditions. 27 experiments were conducted by changing the cutting conditions in each level.

TABLE I
LEVELS OF CUTTING CONDITIONS

Input Parameters	Level		
	A	B	C
Speed (rpm)	120	240	360
Feed (mm/rev)	0.1	0.2	0.3
Depth of cut(mm)	0.6	0.9	1.2

B. Surface Roughness Measurement

The surface roughness of the machined parts is measured using the conventional stylus instrument. A Taylor- Hobson surtronic 3 + instrument was used in our work to measure the average roughness value (Ra) .The cut off length was fixed as 0.8mm for measuring the surface roughness. The measured surface roughness values are tabulated in the Table 3. In order to accomplish training phase, surface roughness values are classified as in Table 2.

TABLE II
CLASS LABELS

Class	Symbol	Surface Roughness Range(μm)
Very Very Low	vvl	0.5-1.0
Very Low	vl	1.01-1.5
Low	l	1.51-2.0
Medium	m	2.01-2.5
High	h	2.51-3.0
Medium high	mh	3.01-3.5
Very High	vh	3.51-4.0
Very Very High	vvh	4.01-4.5

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C. Image Acquisition and Image preprocessing

The machine Vision system consists of a WATEC 902B monochrome CCD camera, frame grabber and interface software. A "Navistar 9000 series "zoom lens was attached with the camera for better magnification. The machined samples were kept stationary under the camera keeping position and zoom level unchanged. The surface images are captured and stored in the computer system. The image preprocessing was carried out in MATLAB R2009b software. The following steps have been carried out for the image pre-processing. They are; Morphological opening with 3x3 masks, Image Subtraction and Contrast Adjustment.

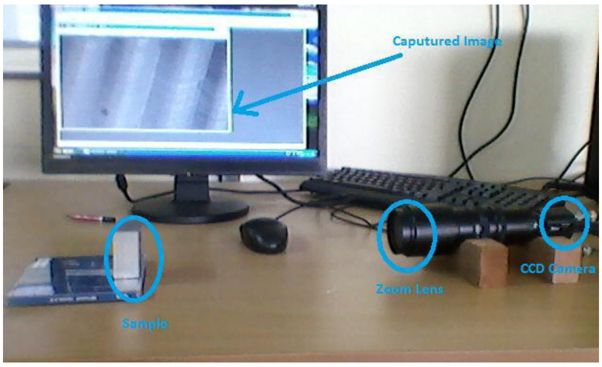

Figure 1 Experimental set up

III FEATURE EXTRACTION

Feature Extraction is the computation of specific measures that define the signal. The image features are taken from samples at different cutting conditions become input to the classifier in this study. The features are application dependent and one has to choose a good set of features for better classification. This process is called feature extraction.

A. Grey Level Co-occurrence Matrix (GLCM)

Texture analysis is the quantification technique that uses an image for extracting texture properties. It is the basically applied to image processing operations such as classification, segmentation and synthesis of textured images. Grey Level Co-occurrence Matrix is one of the famous methods in texture analysis. The Grey level Co-Occurrence matrix is based on the estimation of second order joint conditional probability density functions. The probability describes how often one gray tone will appear in a specified spatial relationship to another gray tone on the image. GLCM is a matrix S that contains the relative frequencies with two pixels: one with gray level value i and the other with gray level j-separated by distance d at a certain angle θ occurring in the image. Given an image window W(x, y, c), for each discrete values of d and θ, the GLCM matrix S(i, j, d, θ) is defined as follows. An entry in the matrix S gives the number of times that gray level i is oriented with respect to gray level j such that W(x1, y1)=i and W(x2, y2)=j, then (x2,y2)=(x1,y1)+(d cosθ + d sinθ). We used d={5 10 15 20}and θ={0° 45° 90° 135°}.There are four GLCM texture features are extracted, they are Contrast, Correlation, Energy and Homogeneity. Table. 3 depict the extracted features and its class.

TABLE III
SAMPLE TRAINING DATA SET

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Run No:	Contrast	Correlation	Energy	Homogeneity	Surface Roughness (Ra) µm	Class label
1	3.9631	-0.0182	0.2055	0.6282	4.36	vvh
2	7.9721	-0.0041	0.1292	0.5392	3.28	mh
3	4.1442	0.0486	0.2007	0.6219	2.56	h
4	6.8816	0.1624	0.1822	0.607	2.72	h
5	5.9173	0.1022	0.199	0.62	1.16	vl
6	5.1407	0.0848	0.2063	0.6244	3.44	mh
7	6.2108	0.0836	0.2087	0.6174	3.4	mh
8	4.4348	0.0418	0.2376	0.6435	1.23	vl
9	5.9383	0.0263	0.1788	0.5976	1.1	vl
10	6.8869	-0.0076	0.1361	0.552	2.96	h
11	8.5669	-0.0144	0.1166	0.5227	2.56	h
12	6.2499	0.0246	0.1781	0.5945	2.58	h
13	6.2145	0.0206	0.1764	0.5778	3.32	mh
14	6.1398	0.0312	0.1618	0.5817	2.16	mh
15	8.004	0.6116	0.2044	0.7081	1.32	vl
16	6.1389	0.0118	0.2072	0.612	4.32	vvh
17	4.6432	0.7705	0.2218	0.7541	3.84	vh
18	5.5766	0.0359	0.2409	0.6511	3.88	vh
19	6.5538	0.6689	0.204	0.7158	3.56	vh
20	7.8645	-0.0193	0.1366	0.5488	2.6	h
21	6.9891	0.0337	0.1494	0.5629	1.96	l
22	5.4459	-0.0486	0.1905	0.5961	1.2	vl
23	7.9747	0.0061	0.1466	0.5568	1.14	vl
24	8.8893	-0.027	0.1483	0.5504	1.84	l
25	8.6527	-0.0072	0.1524	0.562	1.068	vl
26	8.8993	-0.0354	0.1515	0.5526	1.72	l
27	8.5457	0.0149	0.1466	0.5521	0.888	vvl

IV DATA MINING

A. Decision Tree

Decision tree is one of the data mining techniques used in the industry to retrieve valuable knowledge from the available data set including surface roughness data. Decision tree used in this article in the classification of surface roughness data for future events. A standard tree induced with C5.0 (or possibly ID3 or C4.5) consists of a number of branches, one root, a number of nodes and a number of leaves. One branch is a chain of nodes from root to a leaf, and each node involves one attribute. The occurrence of an attribute in a tree provides the information about the importance of the associated attribute. A WEKA implementation of C4.5 algorithm" J48 algorithm" is a widely used in constructing decision trees. Decision tree algorithm (C4.5) has two phases: building and pruning.

B. Naïve Bayes Classifier

The Naïve Bayes algorithm is a classification algorithm based on Bayes rule that assumes Y is the function of n conditionally independent attributes X1, . . .,Xn. This assumption dramatically simplifies the representation of P(X|Y),and the problem of estimating it from the training data. The minimum number of objects was used to classification surface roughness data set. V RESULTS AND DISCUSSION In this article, decision tree algorithm was used. The input of the decision tree is set of GLCM features. The output of the algorithm is a decision tree as shown in fig. 2. In order to avoid over fitting of data and higher percentage classification accuracy, a set of experiments were done to model the classifier. Fig.3 shows the relationship between number of objects and classification accuracy. The number of objects required to form a class was varied from 1 to 324 with a step of 27. The corresponding classification accuracies were plotted. It is observed that 135 objects classification model has highest percentage classification accuracy. Since minimum number of objects are required to form class so that it has minimum branching. Hence, it is logical to choose 135 objects model to classify test dataset. The model was designed keeping confidence factor with default value(0.25) as the confidence factor does not influence the classification accuracy[6].The classification result of C4.5 algorithm is also depicted in the form of confusion matrix as shown in fig. 3. Fig.4 shows the confusion matrix of the classification of GLCM features for surface roughness classifications using Naïve Bayes algorithm. On observing confusion matrix of decision tree, misclassification among classes was high in Naïve Bayes compared to decision tree. Decision tree classification technique found to have correctly classified instances with respect

to each class except for high(h), medium high(mh) and very low(vl) classes. Naïve Bayes classification technique found to have misclassification among almost all the classes.

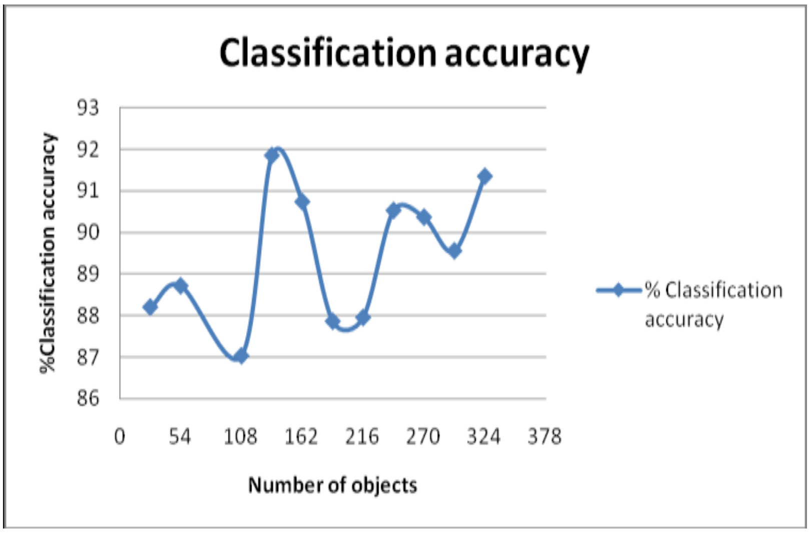

Figure 2 Number of objects vs %classification accuracy of decision tree

V CONCLUSION

This article deals with machining learning approach for automatic classification of surface roughness of end milled Aluminum alloy samples from its image features. There are eight different classes were considered. Set of GLCM features have been extracted and used as input for decision tree and Naïve Bayes classifiers. From the results and discussions, one can conclude that decision tree classification using J48 algorithm can effectively applied for practical applications of classification of end milled Aluminum alloys. Also, It is understood from the confusion matrix, J48 algorithm classifies the given data set better than Naïve Bayes algorithm.

a	b	c	d	e	f	g	<-- classified as
9	0	0	0	1	0	0	a = vvh
0	23	1	1	0	0	0	b = mh
1	2	26	0	1	0	0	c = h
1	1	0	33	0	0	0	d = vl
0	0	0	1	14	0	0	e = vh
0	0	1	0	0	14	0	f = l
0	0	0	0	0	0	5	g = vvl

a	b	c	d	e	f	g	<-- classified as
4	1	0	4	0	1	0	a = vvh
7	7	1	4	1	5	0	b = mh
1	9	6	9	0	5	0	c = h
2	2	1	17	3	10	0	d = vl
2	1	1	9	2	0	0	e = vh
0	0	0	2	0	13	0	f = l
0	0	0	0	0	0	5	g = vvl

Figure 3 Confusion matrix of decision tree Figure 4 Confusion matrix of Naïve Bayes Classifier

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